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Abstract

Long memory in variance or volatility refers to a slow hyperbolic decay in auto-correlation functions of the squared or log-squared returns. GARCH models extensively used in empirical analysis do not account for long memory in volatility. The present paper examines the issue of long memory in volatility in the context of Indian stock market using the fractionally integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) model. For the purpose, daily values of 38 indices from both National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) are used. The results of the study confirm presence of long memory in volatility of all the index returns. This shows that FIGARCH model better describes the persistence in volatility than the conventional ARCH-GARCH models.

Key words: Fractional integration, Long memory, Volatility, FIGARCH, hyperbolic decay, Indian Stock Market, NSE, BSE.
JEL Classification: G12, G14, C58

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1. Introduction

The rapid growth of emerging markets like India since the recent past, and increasing importance of the Indian equity market in the global finance have attracted the attention of investors across the globe. As a result, there has been increasing interest among researchers, investors, and practitioners to understand the behavior of the Indian stock market. Thin-trading, high volatility and various frictions generally characterize stock markets of emerging economies. Volatility in stock returns has been considered as an indicator of vulnerability of financial markets and the economy. Volatility forecasting has also been essential for option pricing and value at risk modelling. Absolute returns, squared and log-squared returns used as proxies of returns volatility in empirical studies.

A large volume of literature focuses on modeling volatility. The unconditional volatility models which assume that volatility would be constant are the oldest one found in the literature. Later, scholars have recognized the fact that volatility cannot be constant as it evolves overtime and shocks persist for a long time. Hence, several conditional volatility models have been proposed to capture the volatility persistence properties in conditional variance. Autoregressive conditional heteroscedasticity (ARCH) and generalized ARCH (or GARCH) proposed by Engle (1982) and Bollerslev (1986) respectively, are the most popular among them. However, these models do not account for long memory in volatility. The autocorrelation of the returns appears to decay at a slower rate. Slow mean-reverting hyperbolic rate decay in autocorrelation functions of squared, log-squared returns defined as long memory in variance or volatility process.

Granger and Joyeux (1980) and Hosking (1981) have introduced a model of fractional difference in the mean process which is known as autoregressive fractionally integrated moving average (ARFIMA). On similar lines, Baillie *et al* (1996) proposed a fractionally integrated

GARCH (or FIGARCH) model which introduces fractional difference operator in the conditional variance function. The presence of long memory in conditional variance masks the true dependence structure (Mendes and Kolev 2006) and perfect arbitrage is not possible when returns display a long-range dependence (Mandelbrot 1971). Furthermore, the derivative pricing models, which are based on Brownian motion and, martingale process also become inappropriate in the presence of long-range dependence. Hence, presence of long memory has important theoretical and practical implications.

The issue of long memory though has important implications for the theory of finance and practical applications, has not received attention in India. In the light of this backdrop, the present paper tests the presence of long memory in volatility in the Indian stock returns by using FIGARCH model. The study may be justified on many grounds. This is the first study which examines the issue of long memory in volatility in the Indian context. The Indian economy has registered a tremendous growth in the recent past and the financial sector reforms coupled with market microstructure changes have given much impetus for the growth of the stock market. The economy in the past decade has not only witnessed rapid growth, but also faced financial crisis at different points of time leading to erratic fluctuations in the stock prices. This study which uses updated and disaggregate data set covering the period of such structural changes is relevant. The multiple choice of the indices from the NSE and BSE helps to assess the sensitivity of empirical results with respect to their different composition.

The rest of the paper organized as follows: Section 2 presents a brief review of previous work on long memory in volatility primarily from the emerging markets. The methodology followed in the study is described in section 3 and section 4 discusses the empirical results for the NSE and the BSE. The last section presents concluding remarks.

2. Review of Previous Work

There are several studies which have focused on long memory in volatility in developed markets particularly the US (See, Ding *et al* 1993; Crato and Lima 1994; Ding and Granger 1996; Andersen and Bollerslev 1997; Granger *et al* 1997; Comte and Renault 1998; Lobato and Savin 1998; Andersen *et al* 2003, Andreano 2005, Gurgul and Wojtowicz 2006). However, there has been little focus on the issue of long memory in the context of emerging markets barring a few studies in the recent past, which have provided some evidence of long memory in volatility. The present section presents a brief review of previous work particularly the recent studies from emerging markets. Cavalcante and Assaf (2005) have reported strong dependence in absolute and squared returns series of Brazilian market during the period 1997- 2002 . Using the data between 1995 and 2005 of 12 emerging markets, Mendes and Kolev (2006) have found strong presence of long memory in volatility in these markets. MENA markets namely, Egypt, Jordon, Morocco and, Turkey have also exhibited significant long memory in volatility, but long memory was not because of sudden shifts in variance (Assaf, 2007). Kang and Yoon (2008) who argue that the long memory in volatility is inherent in data generating process and it is not because of any shocks, support this view. In contrast, Korkmaz *et al* (2009) prove that unfiltered index returns in Turkey display strong evidence of long memory but after treating structural breaks properly, the results show weak evidence. The study thus puts that long memory in volatility is the result of occurrence of structural breaks. Oh *et al* (2006) have focused on eight international indices both from developed and emerging markets[1] and suggested strong evidence of long memory.

The studies from Turkey provide evidence of long memory in returns volatility [2] (Killic 2004; Kasman and Torun 2007; DiSario *et al* 2008). Floros *et al* (2007) establish long memory in volatility for Portuguese stock returns. Empirical evidence of long memory in volatility for

[1] These indices are namely, S & P 500, NASDAQ, Hengseng, Nikkie 225, DAX, CAC40, FTSE 100 and KOSPI.
[2] Studies relating to Turkey used data on Istanbul Stock Exchange.

African markets are mixed. Jefferis and Thupayagale (2008) have offered evidence of long memory in volatility for South Africa and Zimbabwe, whereas no such evidence were found in Botswana. In their investigation of African markets, McMillan and Thupayagale (2009) found evidence of long memory in volatility in seven of eleven African markets researched. Illiquidity and trading conditions in these markets were considered as factors responsible for such long memory. Against the backdrop of economic reforms in South Africa, McMillan and Thupayagale (2008) have investigated the issue of long memory in volatility. For the purpose, the study has divided the data into the pre and post reform period. The results suggested long memory in volatility for both pre and post reform period. They conclude that the behaviour of stock returns in South Africa continued to be driven by risk.

The evidence from emerging markets provide mixed evidence of long memory in volatility process. However, there has been no comprehensive study of long memory in volatility in India, which is one of the fastest growing emerging markets. Hence, the present paper is devoted to the issue of long memory in volatility in the two premier Indian stock exchanges namely, National Stock Exchange (NSE) and Bombay Stock Exchange (BSE).

3. Data and Methodology

3.1 Data

The present paper uses the daily values[3] of 18 indices traded at NSE and 20 at BSE for period 1 April 1997 to 31 January 2011. Table 1 presents the list of indices with sample period of each index. The data range is different for certain indices, as NSE and BSE launched indices at different points of time. The selected indices have enough number of observations to perform

[3] Taylor (2005) suggests that time interval between prices should be sufficient enough, so that trade takes place in most intervals. Selecting daily values will be both appropriate and convenient.

time-series econometrics models to get interesting results [4]. This comprehensive and disaggregated data sample reflects sensitiveness of results to the composition of indices and relative performance of the indices. The daily index values of the NSE and BSE are collected from the official websites of the NSE and the BSE.

3.2 Methodology

Squared returns or absolute returns, which are used as measure of volatility, sometimes have autocorrelations that decay at a slow hyperbolic rate. The conventional ARCH models are incapable to capture the slow decay of autocorrelation function in conditional variance because shocks to the GARCH process decays quickly at an exponential rate. Hence, the present study uses FIGARCH model, which captures a slow hyperbolic rate of decay for the lagged squared innovation in the conditional variance function. A brief description of the model is given here. The standard GARCH (*p, q*) model in ARMA for squared errors can be written as

$$[1-\alpha\,(\mathrm{B})-\beta(\mathrm{B})\,]\,\varepsilon_t^2=\omega+[1-\beta(\mathrm{B})]\,\nu_t \qquad \ldots(1)$$

where B is the back shift operator, $\alpha(\mathrm{B})$, $\beta(\mathrm{B})$ are polynomials in B and $\nu_t \equiv \varepsilon_t^2-\sigma_t^2$ *is* mean zero serially uncorrelated error, ε_t^2 is the squared error of the GARCH process and σ_t^2 is its conditional variance. Thus the $\{\nu_t\}$ process is integrated as the "innovations" for the conditional variance. All the roots of the polynomials $[1-\alpha(\mathrm{B})-\beta(\mathrm{B})]$ and $[1-\beta(\mathrm{B})]$ are constrained to lie outside the unit circle in order to ensure stability and covariance stationary of the $\{\varepsilon_t\}$ process. When autoregressive lag polynomial, $1-\alpha(\mathrm{B})-\beta(\mathrm{B})$ contains a unit root, the model becomes integrated GARCH or IGARCH model of Engle and Bollerslev (1986). This is given by

$$\phi(\mathrm{B})(1-\mathrm{B})\varepsilon_t^2=\omega[1+\beta(\mathrm{B})]\nu_t \qquad \ldots(2)$$

[4] Taylor (2005) opines that at least four years of daily values (more than 1000) observation are required to obtain interesting results.

where $\phi(B) = 1 - d(B) - P(B)$. Similar to ARFIMA process for the mean, by introducing a difference operator $(1 - B)^{\bar{d}}$ in equation (2), fractionally integrated GARCH or FIGARCH (*p q d*) model can be specified as

$$\phi(B)(1 - B)^{\bar{d}}\, \varepsilon_t^2 = \omega + [1 - \beta(B)]\, v_t \qquad \ldots (3)$$

where $\phi(B)$ and $\beta(B)$ are polynomial in B of orders p and q respectively, and β's, ω and d are parameter to be estimated. In equation (3), ν_t is a mean-zero, serially uncorrelated process, and $0<d<1$. The FIGARCH captures a slow hyperbolic rate of decay for the autocorrelations of ε_t. The FIGARCH model reduces to GARCH when $d = 0$ and to the IGARCH when $d = 1$.

4. Empirical Results

The present section discusses the empirical results of the study. Log returns are used for empirical analysis. Tables-2 and 3 report the descriptive statistics for index returns of NSE and BSE respectively. The mean returns for all indices are positive with the sole exception of CNX Reality, which has negative mean returns. The index means returns on an average are significantly higher for smaller and medium sized indices than high capitalized indices and thus support the view that small index generally have higher returns. The BSE Small, Bankex, BSE Midcap, BSE Metal and BSE CG topped the list in average returns. The volatility as indicated by standard deviation ranges between 0.036 (CNX Reality) and 0.001 (BSE Oil & Gas). The returns of all indices display negative skewness implying that the returns are flatter to the left compared to normal distribution. The null hypothesis of skewness coefficients are zero is rejected at the conventional significance level. Further, kurtoses of the returns are found highly significant indicating that returns are leptokurtic. The hypothesis of normality is further rejected based on Jarque-Bera test, which has yielded significant statistics for all returns series.

The presence of long memory in variance is tested by estimating FIGARCH model of Baillie *et al* (1996) by using quasi-maximum likelihood estimate (QMLE), which is a consistent method[5]. For a comparison purpose, GARCH (1, 1) model is estimated and the results of GARCH (1, 1) estimation for NSE and BSE are presented in tables 4 and 5 respectively. It is evident from the tables that the ARCH (lagged squared residuals, α) and GARCH (lagged conditional variance, β) coefficients are statistically significant for all the indices of NSE and BSE. The significant coefficients demonstrate volatility clustering effect and consequently imply that conditional variance might changes over time. The significant GARCH coefficient indicates that conditional variance depends on its own lagged values.

The persistent estimate $\hat{\alpha} + \hat{\beta}$ is close to unity for the indices of both NSE and BSE, indicating a highly persistent tendency for the volatility response to shocks (see table 4 & 5). The results confirm to the tendency that large (small) returns, positive or negative would lead to large (small) change. The Ljung-Box (1978) statistics for standardized residuals and squared residuals reported in table 4 and 5, give the impression that the model adequately describes the volatility persistence. Furthermore, since the sum of coefficients is very close to unity, one can infer that IGARCH model better describes the volatility persistence.

However, it is not the case if the shocks decay hyperbolically at a slower rate. Hence, Baillie *et al* (1996) caution that such kind of results may lead one to infer that the IGARCH model provides a satisfactory description of the volatility process. Keeping this caveat in mind, the study estimates FIGARCH model and the results are reported in table 6 and 7 for NSE and BSE respectively. The results for NSE indices show that the value of fractional differencing parameter d is less than 0.5 for S & P CNX Nifty, CNX Nifty Junior, S & P CNX Defty, CNX Midcap and CNX Bank Nifty, CNX Reality, CNX FMCG, CNX MNC, CNX Pharma, CNX PSE, CNX PSU Bank, CNX Service sector (see table 6). In other words, 13 out of 18 indices traded at NSE indicate long memory in volatility. For BSE, it is evident from table 7 that the

[5] Baillie *et al* (1996) also have shown that QMLE method performs better than other methods to estimate the model

estimated value of *d* is less than theoretical value ($0<d<0.5$) for all the indices with the exception of BSE Small and Dol 30. FIGARHC model becomes covariance stationary GARCH model for $d=0$ and when $d=1$, the model becomes non-stationary GARCH. Thus the major merit of FIGARH ($0<d<1$) model is that it sufficiently allow the intermediate range of persistence. Hence, it is important to note here that the value of the *d* for other indices is greater than zero but less than one and thus FIGARCH better captures such intermediate range of persistence. Furthermore, the significant *d* values reported in tables 6 and 7 reject the null hypothesis that $d=1$ indicating an fractionally integrated process and obviously $d=0$ also gets rejected as d is greater than 0 for all the indices selected in the study. Thus, the FIGARCH model adequately describes the persistence of shocks in variance.

The results thus clearly suggest that most of the stock indices exhibit long memory volatility. It implies that the shocks to conditional variance decays at a slower rate hyperbolically. Furthermore, the significant results of long memory in volatility found in returns show that the conventional model such as GARCH and IGARCH models are not capable to capture such slow rate of decay in autocorrelation. The relative size hypothesis which states that small indices substantially exhibit long memory, has not found support from the empirical evidence of the present study, as long memory properties are found in most of the series.

The stock returns on both NSE and BSE posses long memory in volatility. This indicates possibility of predictable components based on past volatility. The evidence of long memory in volatility indicate persistence of shocks for longer period. Poon and Granger (2003) pointed out that long memory in volatility implies that shock to volatility process would have a long-lasting impact. This highlights the importance of treating long memory in volatility in monetary policy measures. The evidence of this study by and large indicate that long memory models such as FIGARCH is preferable to conventional models for modeling volatility

5. Concluding Remarks

The purpose of this paper is to investigate empirically the presence of long memory in volatility of the Indian stock market, in the light of several macro economic and market microstructure changes. The study has used 38 indices from two premier stock exchanges in India, NSE and BSE. The study has empirically found substantial evidence of fractional integration which shows the existence of long memory in Indian stock market volatility. In other words, there exists a tendency for the volatility response to shocks to display a long memory as shocks hyperbolically decay at a slow rate. Further, the evidence of long memory in volatility across the indices suggests that FIGARCH model adequately describes the persistence than the conventional ARCH class models. Therefore, in the backdrop of the present study, long memory models such as FIGARCH are recommended for volatility forecasting. The use of high frequency data at (minute frequency) and individual stocks composing different indices for further analysis would be helpful in understanding the dynamics of market and to explain interaction between volatility persistence and market microstructure variables.

Table 1: Data Sample

S.No	NSE Indices	Time period	BSE Indices	Time period
1	S & P CNX NIFTY	01/04/1997 – 31/01/2011	SENSEX	01/04/1997 – 31/01/2011
2	CNX NIFTY JUNIOR	01/04/1997 – 31/01/2011	BSE100	01/04/1997 – 31/01/2011
3	S & P CNX DEFTY	01/04/1997 – 31/01/2011	BSE200	01/04/1997 – 31/01/2011
4	CNX100	01/01/2003 – 31/01/2011	BSE500	01/02/1999 – 31/01/2011
5	CNX500	07/06/1999 – 31/01/2011	BSE MIDCAP	01/04/2003 – 31/01/2011
6	CNX MIDCAP	01/01/2001 – 31/01/2011	BSE SMALLCAP	01/04/2003 – 31/01/2011
7	NIFTY MIDCAP 50	01/01/2004 – 31/01/2011	DOL30	01/04/1997 – 31/01/2011
8	S & P ESGINDIA	03/01/2005 – 31/01/2011	AUTO	01/02/1991 – 31/01/2011
9	CNX BANK NIFTY	01/01/2000 - 31/01/2011	BANKEX	01/01/2002 – 31/01/2011
10	CNX INFRA	01/01/2004 – 31/01/2011	CD	01/02/1999 – 31/01/2011
11	CNX REALITY	02/01/2007 – 31/01/2011	CG	01/02/1999 – 31/01/2011
12	CNX ENERGY	01/01/2001 – 31/01/2011	FMCG	01/02/1999 – 31/01/2011
13	CNX FMCG	01/04/1997 – 31/01/2011	HC	01/02/1999 – 31/01/2011
14	CNX MNC	01/04/1997 – 31/01/2011	IT	01/02/1999 – 31/01/2011
15	CNX PHARMA	01/01/2001 – 31/01/2011	METAL	01/02/1999 – 31/01/2011
16	CNX PSE	01/04/1997 – 31/01/2011	OIL & GAS	01/02/1999 – 31/01/2011
17	CNX PSUBANK	01/01/2004 – 31/01/2011	POWER	03/01/2005 – 31/01/2011
18	CNX SERVICE	01/06/1999 – 31/01/2011	PSU	01/02/1999 – 31/01/2011
19			REALITY	02/01/2006 – 31/01/2011
20			TECK	02/01/2001 – 31/01/2011

The table presents data sample. 18 indices from NSE and 20 from BSE including sectoral indices are chosen for the study. The reason for different range of data for different indices is that indices are launched by NSE and BSE at different points of time.

Table 2: Summary Statistics for NSE Index Returns

Index	Mean	Std.Dev	Skewness	Kurtosis	Jarque-Bera
S & P CNX NIFTY	0.000503	0.017199	-0.230700	6.332143	5801.12
CNX NIFTY JUNIOR	0.000682	0.019934	-0.565759	4.378936	2943.87
S & P CNX DEFTY	0.000431	0.018533	-0.122162	7.007511	7073.60
CNX100	0.000837	0.017501	-0.373822	8.366960	5930.39
CNX500	0.000593	0.017311	-0.502451	6.126742	4675.40
CNX MIDCAP	0.000768	0.016510	-0.954828	7.010640	5536.96
NIFTY MIDCAP 50	0.000531	0.020287	-0.838225	7.388301	4218.71
S & P ESGINDIA	0.000859	0.017119	-0.376916	6.383459	2587.46
CNX BNIFTY	0.000854	0.021474	-0.202831	5.115589	3037.16
CNX INFRA	0.000631	0.020680	-0.351066	8.409798	5234.50
CNX REALITY	-0.00121	0.036990	-0.403272	5.264935	1193.90
CNX ENERGY	0.000863	0.018704	-0.476710	8.237038	7210.97
CNX FMCG	0.000540	0.015995	-0.115274	4.175435	2516.73
CNX MNC	0.000480	0.015145	-0.266808	4.842223	3413.43
CNX PHARMA	0.000614	0.013657	-0.389232	5.398858	3120.41
CNX PSE	0.000464	0.019229	-0.268446	5.633180	4605.68
CNX PSUBANK	0.000814	0.024186	-0.316408	4.920879	1797.95
CNX SERVICE	0.000652	0.021416	-0.339888	4.609145	2639.12

The descriptive statistics for 18 indices of NSE are given in the table. The null of skewness and kurtosis =0, is significantly rejected for all the indices and Jarque-Bera test statistics given in last column significantly rejects the null of normality.

Table 3: Summary Statistics for BSE Index Returns

Index	Mean	Std.Dev	Skewness	Kurtosis	Jarque-Bera
SENSEX	0.000487	0.017310	-0.140377	5.210795	3905.40
BSE100	0.000541	0.017695	-0.291974	4.947919	3560.01
BSE200	0.000558	0.017357	-0.375777	5.274139	4070.36
BSE500	0.000656	0.017414	-0.467928	5.462937	3832.25
BSE MIDCAP	0.001039	0.016974	-1.054025	6.948490	4297.11
BSE SMALLCAP	0.001185	0.017916	-0.965442	4.114001	1683.24
DOL30	0.000416	0.018541	-0.164952	4.940525	3517.25
AUTO	0.000729	0.016866	-0.333561	3.013231	1188.98
BANKEX	0.001098	0.021408	-0.106458	5.792133	3174.64
CD	0.000598	0.021452	-0.275153	3.347556	1436.22
CG	0.000870	0.019984	-0.058610	6.639774	5503.35
FMCG	0.000405	0.015463	-0.116346	3.779671	1789.52
HC	0.000611	0.015173	-0.285882	4.421422	2480.34
IT	0.000618	0.027327	-0.306434	5.577057	3928.33
METAL	0.000928	0.024369	-0.326885	3.598843	1670.15
OIL & GAS	0.000751	0.000751	-0.300633	6.760123	5749.92
POWER	0.000669	0.020424	-0.064553	6.876123	2975.81
PSU	0.000723	0.019067	-0.321958	6.520650	5355.95
REALITY	0.000417	0.034722	-0.475230	5.670762	1734.32
TECK	0.000537	0.021027	-0.498345	7.538577	5907.63

The descriptive statistics for 20 indices of BSE are given in the table. The null of skewness and kurtosis =0, is significantly rejected for all the indices and Jarque-Bera test statistics given in last column significantly rejects the null of normality.

Table 4: Estimates of GARCH Model for NSE Index Returns

Index	Mean	C	α	β	Q(20)	Q^2(20)
S & P CNX NIFTY	0.001 (0.00)	0.000 (0.00)	0.149 (0.00)	0.829 (0.00)	66.40 (0.00)	10.92 (0.94)
CNX NIFTY JUNIOR	0.001 (0.00)	0.000 (0.00)	0.165 (0.00)	0.821 (0.00)	129.80 (0.00)	20.96 (0.39)
S & P CNX DEFTY	0.001 (0.00)	0.00 (0.00)	0.150 (0.00)	0.828 (0.00)	64.88 (0.00)	10.03 (0.96)
CNX100	0.001 (0.00)	0.000 (0.01)	0.149 (0.00)	0.839 (0.00)	46.11 (0.00)	16.40 (0.69)
CNX500	0.001 (0.00)	0.000 (0.00)	0.163 (0.00)	0.824 (0.00)	97.26 (0.00)	13.09 (0.87)
CNXMIDCAP	0.001 (0.00)	0.000 (0.01)	0.199 (0.00)	0.784 (0.00)	142.54 (0.00)	20.34 (0.43)
NIFTY MIDCAP 50	0.001 (0.00)	0.000 (0.03)	0.190 (0.00)	0.810 (0.00)	77.10 (0.00)	17.44 (0.62)
S & P ESG INDIA	0.001 (0.00)	0.000 (0.02)	0.173 (0.00)	0.825 (0.00)	39.83 (0.00)	10.26 (0.96)
CNX BNIFTY	0.001 (0.00)	0.000 (0.01)	0.103 (0.00)	0.880 (0.00)	72.49 (0.00)	24.81 (0.20)
CNX INFRA	0.001 (0.00)	0.000 (0.05)	0.162 (0.00)	0.837 (0.00)	60.11 (0.00)	14.13 (0.82)
CNX REALITY	0.000 (0.75)	0.000 (0.06)	0.114 (0.00)	0.874 (0.00)	55.66 (0.00)	9.31 (0.97)
CNX ENERGY	0.001 (0.00)	0.00 (0.06)	0.124 (0.00)	0.865 (0.00)	36.87 (0.01)	12.55 (0.89)
CNX FMCG	0.000 (0.00)	0.000 (0.00)	0.149 (0.00)	0.816 (0.00)	39.63 (0.00)	25.20 (0.19)
CNX MNC	0.001 (0.00)	0.000 (0.00)	0.169 (0.00)	0.802 (0.00)	58.03 (0.00)	23.12 (0.28)
CNX PHARMA	0.000 (0.00)	0.000 (0.01)	0.186 (0.00)	0.723 (0.00)	58.59 (0.00)	12.67 (0.89)
CNX PSE	0.000 (0.00)	0.000 (0.02)	0.110 (0.00)	0.884 (0.00)	95.66 (0.00)	11.81 (0.92)
CNX PSUBANK	0.001 (0.01)	0.000 (0.09)	0.093 (0.00)	0.885 (0.00)	49.03 (0.00)	25.41 (0.18)
CNX SERVICE	0.001 (0.00)	0.000 (0.00)	0.149 (0.00)	0.842 (0.00)	76.29 (0.00)	14.81 (0.78)

The table reports GARCH (1,1) estimates for indices from NSE. C denotes intercept in the variance equation, α is estimated lagged squared residual (ARCH coefficient), and *β,* the lagged variance (GARCH coefficient). The Q(20) and Q^2(20) refer to the Ljung-Box portmanteau tests for serial correlation in the standardized and squared standardized residuals up to 20 lags. The values in the parentheses represent corresponding significance level.

Table 5: Estimates of GARCH Model for BSE Index Returns

Index	Mean	C	α	β	Q(20)	Q^2(20)
SENSEX	0.001 (0.00)	0.000 (0.00)	0.138 (0.00)	0.843 (0.00)	72.87 (0.00)	17.06 (0.64)
BSE100	0.001 (0.00)	0.000 (0.00)	0.157 (0.00)	0.824 (0.00)	94.65 (0.00)	17.28 (0.63)
BSE200	0.001 (0.00)	0.000 (0.00)	0.161 (0.00)	0.821 (0.00)	99.1 (0.00)	18.43 (0.55)
BSE500	0.001 (0.00)	0.000 (0.00)	0.170 (0.00)	0.815 (0.00)	97.98 (0.00)	17.33 (0.63)
BSE MIDCAP	0.002 (0.00)	0.000 (0.02)	0.193 (0.00)	0.804 (0.00)	116.3 (0.00)	21.87 (0.34)
BSE SMALLCAP	0.002 (0.00)	0.000 (0.03)	0.208 (0.00)	0.769 (0.00)	166.30 (0.00)	22.81 (0.29)
DOL30	0.001 (0.00)	0.000 (0.00)	0.138 (0.00)	0.841 (0.00)	76.16 (0.00)	14.74 (0.79)
AUTO	0.001 (0.00)	0.000 (0.00)	0.130 (0.00)	0.829 (0.00)	100.49 (0.00)	16.54 (0.68)
BANKEX	0.001 (0.00)	0.000 (0.01)	0.101 (0.00)	0.881 (0.00)	54.40 (0.00)	24.48 (0.22)
CD	0.001 (0.00)	0.000 (0.00)	0.154 (0.00)	0.807 (0.00)	96.13 (0.00)	13.20 (0.86)
CG	0.001 (0.00)	0.000 (0.01)	0.149 (0.00)	0.831 (0.00)	95.98 (0.00)	20.67 (0.41)
FMCG	0.001 (0.01)	0.000 (0.00)	0.153 (0.00)	0.802 (0.00)	24.45 (0.22)	30.16 (0.06)
HC	0.000 (0.00)	0.000 (0.02)	0.161 (0.00)	0.811 (0.00)	91.08 (0.00)	17.55 (0.61)
IT	0.001 (0.00)	0.000 (0.01)	0.130 (0.00)	0.863 (0.00)	43.84 (0.00)	15.14 (0.76)
METAL	0.001 (0.00)	0.000 (0.01)	0.139 (0.00)	0.831 (0.00)	82.90 (0.00)	21.47 (0.36)
OIL & GAS	0.000 (0.00)	0.000 (0.06)	0.100 (0.00)	0.887 (0.000)	55.73 (0.00)	17.90 (0.59)
POWER	0.000 (0.00)	0.000 (0.11)	0.138 (0.00)	0.858 (0.00)	52.72 (0.00)	7.62 (0.99)
PSU	0.000 (0.00)	0.000 (0.03)	0.108 (0.00)	0.885 (0.00)	98.79 (0.00)	12.26 (0.90)
REALITY	0.001 (0.01)	0.000 (0.12)	0.125 (0.00)	0.862 (0.00)	115.76 (0.00)	11.49 (0.93)
TECK	0.001 (0.00)	0.000 (0.00)	0.136 (0.00)	0.852 (0.00)	49.49 (0.00)	10.51 (0.95)

The table reports GARCH (1, 1) estimates for indices from BSE. C denotes intercept in the variance equation, α is lagged squared residual (ARCH coefficient), and β lagged variance (GARCH coefficient). The Q(20) and Q^2(20) refer to the Ljung-Box portmanteau tests for serial correlation in the standardized and squared standardized residuals up to 20 lags. The values in the parentheses represent corresponding significance level.

Table 6: FIGARCH Estimates for NSE Index Returns

Index	Mean	C	β	*d*	Q(20)	Q^2 (20)
S & P CNX NIFTY	0.001 (0.00)	0.000 (0.03)	0.326 (0.00)	0.471 (0.00)	69.50 (0.00)	11.43 (0.93)
CNX NIFTY JUNIOR	0.001 (0.00)	0.000 (0.05)	0.214 (0.00)	0.476 (0.00)	131.66 (0.00)	21.44 (0.37)
S & P CNX DEFTY	0.001 (0.00)	0.000 (0.08)	0.261 (0.00)	0.447 (0.00)	66.11 (0.00)	11.03 (0.94)
CNX100	0.001 (0.00)	0.00 (0.53)	0.708 (0.00)	0.839 (0.00)	48.22 (0.00)	16.81 (0.66)
CNX500	0.001 (0.00)	0.00 (0.36)	0.362 (0.00)	0.530 (0.00)	98.76 (0.00)	13.26 (0.86)
CNXMIDCAP	0.001 (0.00)	0.00 (0.02)	0.248 (0.00)	0.500 (0.00)	138.69 (0.00)	20.26 (0.44)
NIFTY MIDCAP 50	0.001 (0.00)	0.000 (0.09)	0.315 (0.00)	0.542 (0.00)	77.03 (0.00)	15.33 (0.75)
S & P ESG INDIA	0.001 (0.00)	0.00 (0.03)	0.403 (0.00)	0.590 (0.000)	41.84 (0.00)	8.85 (0.98)
CNX BNIFTY	0.001 (0.00)	0.00 (0.42)	0.249 (0.00)	0.390 (0.00)	74.76 (0.00)	17.97 (0.58)
CNX INFRA	0.001 (0.00)	0.000 (0.00)	0.521 (0.00)	0.675 (0.00)	64.12 (0.00)	14.93 (0.77)
CNX REALITY	0.000 (0.75)	-0.000 (0.85)	0.248 (0.00)	0.404 (0.00)	57.34 (0.00)	8.18 (0.99)
CNX ENERGY	0.001 (0.00)	0.00 (0.73)	0.399 (0.00)	0.518 (0.00)	38.52 (0.00)	12.45 (0.89)
CNX FMCG	0.000 (0.00)	0.00 (0.57)	0.103 (0.21)	0.332 (0.00)	42.03 (0.00)	19.56 (0.48)
CNX MNC	0.001 (0.00)	0.00 (0.30)	0.141 (0.01)	0.380 (0.00)	58.70 (0.00)	25.13 (0.19)
CNX PHARMA	0.000 (0.00)	0.00 (0.70)	-0.02 (0.52)	0.26 (0.00)	59.28 (0.00)	12.53 (0.89)
CNX PSE	0.000 (0.00)	0.000 (0.29)	0.348 (0.00)	0.466 (0.00)	93.62 (0.00)	10.08 (0.96)
CNX PSUBANK	0.000 (0.00)	-0.00 (0.76)	0.077 (0.18)	0.276 (0.00)	46.92 (0.00)	15.09 (0.77)
CNX SERVICE	0.001 (0.00)	0.000 (0.64)	0.270 (0.00)	0.453 (0.00)	81.01 (0.00)	13.32 (0.86)

The table reports FIGARCH (1,d,0) estimates for indices from NSE. C denotes intercept in the variance equation, The *d* represent fractional difference in the variance equation. The Q(20) and Q^2(20) refer to the Ljung-Box portmanteau tests for serial correlation in the standardized and squared standardized residuals up to 20 lags. The values in the parentheses represent corresponding significance level.

Table 7: FIGARCH Estimates for BSE Index Returns

Index	Mean	C	β	*d*	Q(20)	Q^2(20)
SENSEX	0.001 (0.00)	0.000 (0.07)	0.356 (0.00)	0.474 (0.00)	78.03 (0.00)	16.66 (0.67)
BSE100	0.001 (0.00)	0.000 (0.13)	0.219 (0.00)	0.478 (0.00)	97.39 (0.00)	17.22 (0.63)
BSE200	0.001 (0.00)	0.000 (0.06)	0.311 (0.00)	0.441 (0.00)	102.01 (0.00)	18.72 (0.53)
BSE500	0.001 (0.00)	0.000 (0.10)	0.299 (0.00)	0.480 (0.00)	99.39 (0.00)	17.67 (0.60)
BSEMID	0.002 (0.00)	0.000 (0.12)	0.227 (0.00)	0.488 (0.00)	114.80 (0.00)	20.48 (0.42)
BSESMALL	0.002 (0.00)	0.000 (0.06)	0.263 (0.00)	0.514 (0.00)	158.7 (0.00)	20.36 (0.43)
DOL30	0.001 (0.00)	0.000 (0.05)	0.388 (0.00)	0.505 (0.00)	81.53 (0.00)	13.80 (0.84)
AUTO	0.001 (0.00)	0.000 (0.77)	0.125 (0.00)	0.310 (0.00)	100.78 (0.00)	17.45 (0.62)
BANKEX	0.001 (0.00)	0.000 (0.41)	0.268 (0.00)	0.410 (0.00)	57.89 (0.00)	20.80 (0.40)
CD	0.001 (0.00)	0.000 (0.48)	0.163 (0.00)	0.356 (0.00)	93.60 (0.00)	12.81 (0.88)
CG	0.001 (0.00)	0.000 (0.07)	0.296 (0.00)	0.478 (0.00)	97.45 (0.00)	18.05 (0.58)
FMCG	0.000 (0.00)	0.000 (0.52)	0.098 (0.00)	0.327 (0.00)	26.60 (0.14)	20.31 (0.43)
HC	0.000 (0.00)	0.000 (0.92)	0.106 (0.01)	0.342 (0.00)	92.04 (0.00)	12.89 (0.88)
IT	0.001 (0.00)	-0.00 (0.22)	0.147 (0.00)	0.350 (0.00)	47.50 (0.00)	9.70 (0.97)
METAL	0.001 (0.00)	0.000 (0.09)	0.294 (0.00)	0.443 (0.00)	85.64 (0.00)	20.46 (0.42)
OIL & GAS	0.000 (0.00)	0.000 (0.98)	0.216 (0.00)	0.358 (0.00)	53.63 (0.00)	12.95 (0.87)
POWER	0.000 (0.00)	0.000 (0.15)	0.393 (0.00)	0.551 (0.00)	56.22 (0.00)	6.83 (0.99)
PSU	0.000 (0.00)	0.000 (0.66)	0.285 (0.00)	0.416 (0.00)	99.81 (0.00)	9.81 (0.97)
REALITY	0.002 (0.01)	0.000 (0.81)	0.228 (0.00)	0.414 (0.00)	111.22 (0.00)	8.51 (0.98)
TECK	0.001 (0.00)	0.000 (0.63)	0.270 (0.00)	0.421 (0.00)	50.57 (0.00)	10.44 (0.95)

The table reports FIGARCH (1,d,0) estimates for indices from BSE. C denotes intercept in the variance equation, The *d* represent fractional difference in the variance equation. The Q(20) and Q^2(20) refer to the Ljung-Box portmanteau tests for serial correlation in the standardized and squared standardized residuals up to 20 lags. The values in the parentheses represent corresponding significance level.

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